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Predicting Tablet Drug Expenditures Using Python-Based Facebook Prophet in Pharmaceutical Installations

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ABSTRACT

The increasing complexity of pharmaceutical logistics requires accurate forecasting to ensure drug availability and minimize the risk of stock shortages. This study aims to develop a forecasting model to predict monthly tablet drug expenditure in the Pharmacy Department. The research stages include problem identification, data collection from historical drug expenditure records, data pre-processing, and implementation of the forecasting model. The method used is Facebook Prophet, which was chosen for its ability to capture seasonal patterns, trends, and holidays in time series data. Model performance evaluation was conducted using Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE). The results showed that the model produced an MAE of 3,621.25 and a MAPE of 4,93%, indicating that the prediction accuracy level was in the good category. These findings prove that the Prophet method is capable of providing reliable results in drug expenditure forecasting. The results of this study are expected to support decision-making in drug requirement planning and improve the efficiency of pharmaceutical logistics management.

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1. Introduction

Technology has become an important part of life, making computers indispensable in various aspects [1], including healthcare. The availability of drugs is a crucial factor in ensuring the quality of healthcare services. Pharmacy Law No. 7 of 1963 states that drugs are substances derived from animals, plants, minerals, or synthetics that are used for treatment when administered in the right dosage and at the right time [2]. In 2020, total paracetamol expenditure amounted to 641,714 tablets, in 2021 it amounted to 592,700 tablets, in 2022 it amounted to 802,500 tablets, in 2022 it amounted to 898,000 tablets, and in 2024 it amounted to 861,930 tablets. However, in practice, drug demand planning in the Pharmacy Installation is still done manually. This method is simple, but it does not take into account trends, seasonal patterns, or fluctuations in demand, so it often causes overstocking when goods pile up, resulting in high and inefficient costs, as well as stockouts that cause patient drug needs to go unmet [3].

Forecasting can be defined as the practice of projecting potential future events by examining trends and patterns derived from past data [4]. Accurate forecasting can reduce storage costs, reduce safety stock, and improve service [5]. The accuracy of forecasting is very important for assessing the reliability and effectiveness of the forecasting model. The accuracy of forecasts can be assessed using error metrics such as Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE) [6],[7].

One relevant modern method is Facebook Prophet, an open-source algorithm developed by Facebook. Prophet is designed to generate accurate predictions and is easy to use by users who are not statistics experts, with the ability to handle missing data, outliers, non-linear trends, and strong seasonal components [8]. A study conducted by Oktavia and Witanti [9] shows that Prophet is effective for data with strong seasonal patterns, while Kwarteng and Andreevich [10] prove that Prophet has a lower MAE (0,74) than SARIMA (2,18) and ARIMA (3,02) in predicting the need for antidiabetic drugs.

Recent studies show that the application of Facebook Prophet and AI-based forecasting approaches is becoming increasingly widespread in the health and pharmaceutical sectors. This model has been proven to improve the accuracy of drug demand predictions and optimize inventory planning through the integration of statistical methods and machine learning [11]. Prophet also demonstrates superior performance in modeling seasonal epidemiological patterns, such as in cases of dengue fever and other infectious diseases, which have fluctuating characteristics over time [12]. Recent systematic reviews also confirm that the use of artificial intelligence for forecasting in the healthcare sector is accelerating significantly, in line with the increasing need for adaptive and data-driven prediction systems [13]. These findings indicate that forecasting tools supported by AI are not only capable of processing complex datasets but also offer more consistent predictive reliability. As a result, their adoption continues to expand as healthcare institutions seek more effective methods for anticipating demand, improving service quality, and strengthening evidence-based decision-making processes.

This study is based on Indonesian Minister of Health Regulation No. 72 of 2016 concerning Pharmaceutical Service Standards in Hospitals, which emphasizes the importance of efficiency and accuracy in drug management [14]. Compared to classical models such as ARIMA and Exponential Smoothing, the Facebook Prophet algorithm has several advantages that make it more adaptive to seasonal and fluctuating pharmaceutical data. Prophet uses an additive model approach with trend, seasonal, and holiday components that can be estimated separately but flexibly [15]. This facilitates interpretation and allows for quick adjustments to changes in data patterns without the need for complex transformations such as in ARIMA. Prophet does not require the assumption of data stationarity, making it more stable when dealing with data with non-linear trends and extreme fluctuations [15]. Prophet's ability to handle missing values and outliers makes it a more reliable choice than classical models, which tend to be sensitive to data disturbances [16]. These advantages make Prophet suitable for predicting medium- to long-term drug expenditures more accurately and efficiently.

Based on this foundation, the present study proposes implementing the Python-based Prophet model to predict tablet drug expenditure within the Pharmacy Installation. Prophet was selected due to its robustness in handling time-series data, its ability to capture seasonal patterns, and its reliability in generating accurate forecasts with minimal parameter tuning. The integration of this model is expected to address common challenges encountered in conventional forecasting, such as inconsistencies in manual calculations, limited analytical capability, and the absence of systematic prediction tools within local government health units.

The key novelty of this research lies in embedding a modern, automated forecasting approach directly into the pharmaceutical planning workflow of a local governmental institution. By incorporating Prophet into the existing system, the study introduces a data-driven mechanism that enhances precision, reduces operational workload, and supports evidence-based decision-making. This advancement offers a more structured and repeatable forecasting process, ensuring that drug demand projections are not only more accurate but also more responsive to fluctuations in consumption patterns.

Ultimately, the proposed approach is expected to improve inventory management, minimize stockouts and overstock conditions, and contribute to more efficient resource allocation in the Pharmacy Installation. This modernization is anticipated to elevate the overall quality of pharmaceutical services delivered to the community.

2. Research Method

2.1. Research Design

This study uses a quantitative approach with *time series forecasting* methods to predict Paracetamol tablet expenditure at the Pharmacy Installation. Quantitative research was chosen because it focuses on the processing of historical numerical data that can be analyzed statistically [17]. The model used is Facebook Prophet, an open-source prediction method developed by Facebook Research, designed to model long-term trends, seasonal patterns, and robust against missing data and outliers [8].

2.2. Research Procedure

The research procedure was carried out through several main stages, namely problem identification, data collection, data pre-processing, application of the Facebook Prophet algorithm, model evaluation, and visualization of results. The following is an illustration of the research procedure flow in Figure 1.

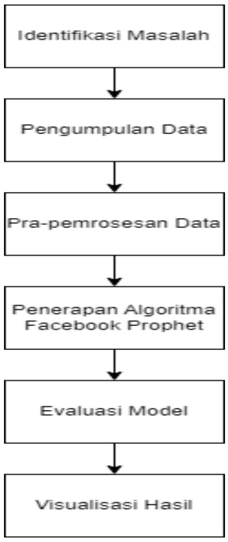

Figure 1. Research Procedure Flowchart

a. Problem Identification

The initial stage of the research began with identifying the problems faced by the Pharmacy Installation. Currently, drug demand planning is still done manually. This approach does not consider trends, seasonality, or fluctuations in drug use, often resulting in overstocking or stockouts [3]. This indicates that a more accurate prediction method based on historical data is needed.

b. Data Collection

The data used is historical data on the expenditure of Paracetamol tablets from 2020 to 2024, obtained through a documentation study at the Pharmacy Installation. The data was recorded in monthly reports containing the number of drug units dispensed each month. The 2020–2021 period covered the COVID-19 pandemic, which caused anomalies in drug demand patterns and potential missing data due to delays in input and changes in pharmacy distribution patterns. Therefore, each data entry was checked to ensure its completeness and consistency. Unrecorded or missing data were identified during the validation process and handled through linear interpolation, which is a mathematical approach to estimating missing values between two known data points based on a straight line relationship.

c. Data Pre-processing

1) Data Validation and Cleaning: This stage is carried out to ensure the completeness and consistency of drug expenditure data from 2020 to 2024. The check includes detecting missing values, duplicate data, and anomalies due to the COVID-19 pandemic (2020–2021) that could potentially affect drug expenditure patterns. Missing values are handled using the linear interpolation method, which

estimates values based on the trends of the two nearest data points. Duplicate data is deleted, while format errors are corrected to match the structure of the Prophet time series.

2) Conversion of date formats to the ISO standard (YYYY-MM-DD).
3) Aggregation of monthly data to produce a consistent time series. All data was standardized into units and underwent monthly aggregation for the purposes of time series analysis [18].
4) Logarithmic Transformation: All drug expenditure values are transformed using the log1p function (natural logarithm of the value plus one) to stabilize data variance and reduce the influence of extreme fluctuations [19].
5) Outlier Detection and Removal: Using the Interquartile Range (IQR) approach, outliers can be identified.. This step aims to reduce the influence of extreme values that do not represent the general pattern of the data [20].
6) Smoothing: The transformed data is then smoothed using the rolling mean method (window = 5) to reduce short-term fluctuations and clarify long-term trend patterns [21].
7) Data Split (Train-Test Split): Historical data from 2020–2023 is used as the training set (80%), while data from 2024 is used as the testing set (20%). This split ensures that the Prophet model is able to generalize to new data and provide more accurate prediction results.

d. Application of the Facebook Prophet Algorithm

1) The pseudocode for the forecasting model is as follows:
Input: Historical drug expenditure data (2020–2024)

Step 1: Load the dataset
Step 2: Pre-processing
Step 3: Train the Prophet model using the training set (2020–2024)
Step 4: Generate forecasts for the next 12 months (2025)
Step 5: Extract trend and seasonal components
Output: 2025 drug expenditure forecast

2) Mathematically, the Prophet model models time series with an additive approach as follows [8]:

$$y(t) = g(t) + s(t) + h(t) + \mathcal{E}_t \tag{1}$$

Description:

a) $y(t)$: Medicine expenditure value at time$t$,
b) $g(t)$: Trend function that describes long-term growth,
c) $s(t)$: Seasonal functions captured by Fourier series,
d) $h(t)$: Holiday or special event component,
e) $\mathcal{E}_t$: Error or noise component.

Seasonal components are modeled with Fourier functions[8]:

$$s(t) = \sum_{n=1}^{N} \left[a_n \left(\frac{2\pi nt}{P} \right) + b_n \sin\left(\frac{2\pi nt}{P} \right) \right] \tag{2}$$

Description:

a) P : Seasonal period (e.g., $P = 12$ for monthly seasonality),
b) N : Fourier order,
c) a_n, b_n : Fourier coefficients studied by the model.

The linear trend component is written as:

$$g(t) = (k + a(t)^T \delta)t + (m + a(t)^T \gamma) \tag{3}$$

Description:

a) k : Growth rate,
b) m : Offset,
c) $a(t)$: Trend change indicator vector at a specific point (changepoints),
d) $\delta\ and\ \gamma$: Trend adjustment parameter at changepoints.

Holidays / Special Events Component: (4)

$$h(t) = Z(t)^T k$$

Description:

a) $Z(t)$: Binary indicator vector (1 if the date is a holiday/special event, 0 if not),

b) k : Holiday impact parameters.

3) Implementation of the Prophet Model

During the implementation stage, the Facebook Prophet model was trained using historical drug expenditure data from 2020 to 2024 that had undergone pre-processing and validation. This model was configured with several key parameters so that the replication process could be carried out consistently. The changepoint_prior_scale parameter was set at 0,05 to regulate the model's sensitivity to trend changes at changepoints [22]. The seasonality_prior_scale value of 10,0 is used to control the strength of the seasonal component in the model, while the interval_width is set to 0,95 to determine the 95% confidence level in the prediction interval [16]. This model also uses a yearly seasonality component with a value of True, while weekly and daily seasonality are disabled because the data is aggregated monthly [23].

In addition, an additional seasonal component called 'monthly' with a period of 12 and a Fourier order of 10 was added to capture the monthly recurring patterns commonly found in drug expenditure patterns [16]. The model was then trained using the training set and produced estimates of drug expenditure for the 2025 period. The forecast results were then compared with actual data using evaluation metrics such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) to assess the model's accuracy [6][24].

The selection of the Facebook Prophet model in this study was based on considerations of efficiency, interpretability, and adaptive capabilities to seasonal and fluctuating pharmaceutical data patterns. Unlike classical models such as ARIMA and Exponential Smoothing, which require stationarity assumptions and complex differentiation processes, Prophet is capable of modeling non-linear trends using a flexible additive approach. In addition, Prophet has the ability to automatically detect change points and handle missing values and outliers without the need for complex data transformations. A study by Kwarteng and Andreevich [10] shows that Prophet produces a lower error rate than ARIMA. Based on these findings, this study focuses on the application of Prophet without involving comparative models such as ARIMA, Holt-Winters, or LSTM, as the main objective is to test the performance of Prophet in the context of drug expenditure.

e. Model Evaluation

The model is evaluated using two commonly used accuracy metrics in time series analysis:

1) Mean Absolute Error (MAE) to calculate the average absolute error [6].
2) Mean Absolute Percentage Error (MAPE) to calculate the relative error in percentage form [24].

The MAPE accuracy criteria are as follows: very good <10%, good = 10%-20%, fair = 20-50%, and inaccurate >50% [25]. Unlike MAPE, which is expressed as a percentage, MAE (Mean Absolute Error) does not have universal criteria because MAE values are highly dependent on the data scale used. MAE shows the average absolute error between actual values and predicted values in the same units as the original data (e.g., drug units, rupiah, or kilograms). The smaller the MAE value, the higher the accuracy level of the forecasting model [26].

f. Visualization of Results

The prediction results are visualized in the form of historical trend graphs, seasonal components, and drug expenditure projections. With data visualization, the available information can be quickly understood through responsive graphs and tables as well as supporting colors [27]. Data visualization also allows for easier information processing, thereby facilitating the decision-making process because the information is packaged in various attractive and easily accessible diagrams [28].

3. Result and Discussion

3.1. Data Collection

The data used in this study is secondary data from monthly expenditure reports on Paracetamol tablets over the past five years (January 2020–December 2024) obtained from the Pharmacy Department. Data was collected using documentation techniques [29]. The following is the historical data on paracetamol 2020-2024 in Table 1.

Table 1. Historical Data on Paracetamol Tablet Expenditures (2020–2024)

Date	Total
31/01/2020	45700
29/02/2020	99814
31/03/2020	97500
30/04/2020	90500
31/05/2020	18000
30/06/2020	2500
31/07/2020	39200
31/08/2020	53800
…	…
31/10/2024	65000
30/11/2024	93300
31/12/2024	70130

3.2. Data Preprocessing

Before the forecasting process is carried out, drug expenditure data first goes through a pre-processing stage to improve data quality and model stability. The first stage is logarithmic transformation of all expenditure values using the log1p function, which is the natural logarithm of the expenditure value plus one. Logarithmic transformation is performed using the log1p function so that the data variance is stable and the effect of extreme fluctuations can be reduced [19], so that the data distribution is closer to normal.

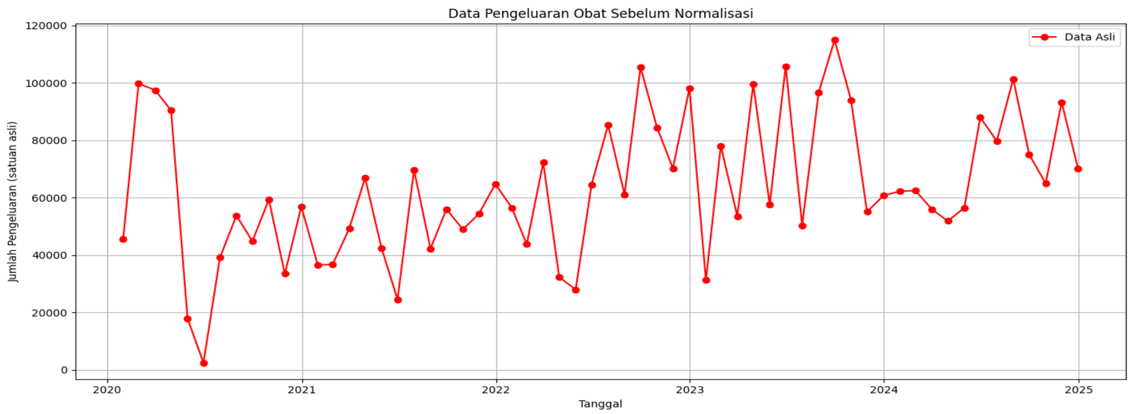

Figure 2. Graph of drug expenditure before normalization

Table 2. Drug expenditure data before normalization

Date	Total
31/01/2020	45700
29/02/2020	99814
31/03/2020	97500
30/04/2020	90500
31/05/2020	18000
30/06/2020	2500
…	…

31/10/2024	65000
30/11/2024	93300
31/12/2024	70130

Figure 2 shows the drug expenditure data before normalization. It can be seen that the data has quite high variation with several sharp spikes (outliers). After the modeling process is complete, the prediction results are returned to their original scale using the expm1 inverse function. The next step is to detect and remove outliers using the Interquartile Range (IQR) method. The lower quartile (Q1) and upper quartile (Q3) values are calculated, then data outside the range $[Q1 - 1.5 \times IQR, Q3 + 1.5 \times IQR]$ are categorized as outliers and removed. This method is widely used in time series data analysis due to its robustness to skewed data distributions [30]. The removal of outliers aims to reduce the influence of extreme values that do not represent the general trend, so that the model can better capture seasonal patterns and trends. The cleaned data is then smoothed using a rolling mean with a window of five (window = 5) to reduce short-term fluctuations and clarify long-term trend patterns [21]. After logarithmic transformation, outlier detection and removal using the IQR method, and smoothing using a rolling mean with a window of five, the data becomes more stable, as shown in Figure 3.

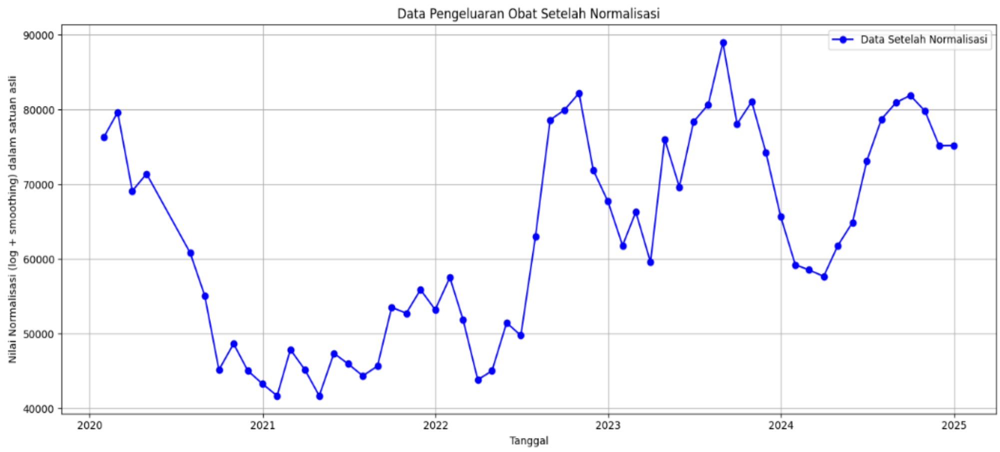

Figure 3. Drug expenditure data after normalization

Table 3. Drug expenditure data after normalization

Date	Total
31/01/2020	76331
29/02/2020	79650
31/03/2020	69120
30/04/2020	71413
31/07/2020	60868
…	…
31/10/2024	79813
30/11/2024	75176
31/12/2024	75202

The normalized data was then divided into two parts, namely the training set and the testing set. The training set was used to build a forecasting model using the Facebook Prophet algorithm, while the testing set was used to evaluate the model's performance. The evaluation was carried out using the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) metrics to measure the level of prediction error of the model against the actual data. This pre-processing stage was carried out to reduce noise, stabilize data patterns, and improve the generalization ability of the model so as to produce smaller error values during the forecasting process.

3.3. Application of the Prophet Model

The processed data was used to train the Facebook Prophet model. The model was trained using five years of expenditure data (2020–2024) and then used to predict expenditure for the next year (January–December 2025). The Prophet model was able to separate the trend and seasonal components, thereby identifying recurring annual patterns in Paracetamol usage. After the model was trained, expenditure predictions were made for the period January–December 2025.

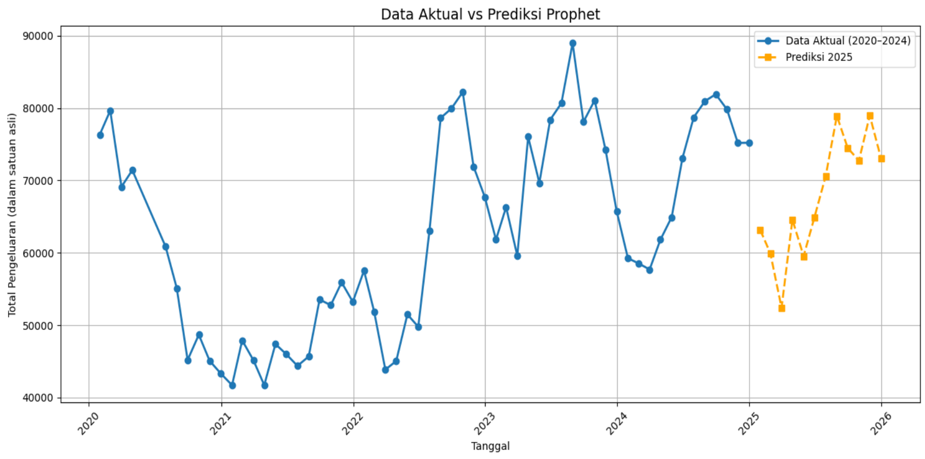

Figure 4. Graph of 2025 Drug Expenditure Prediction Results

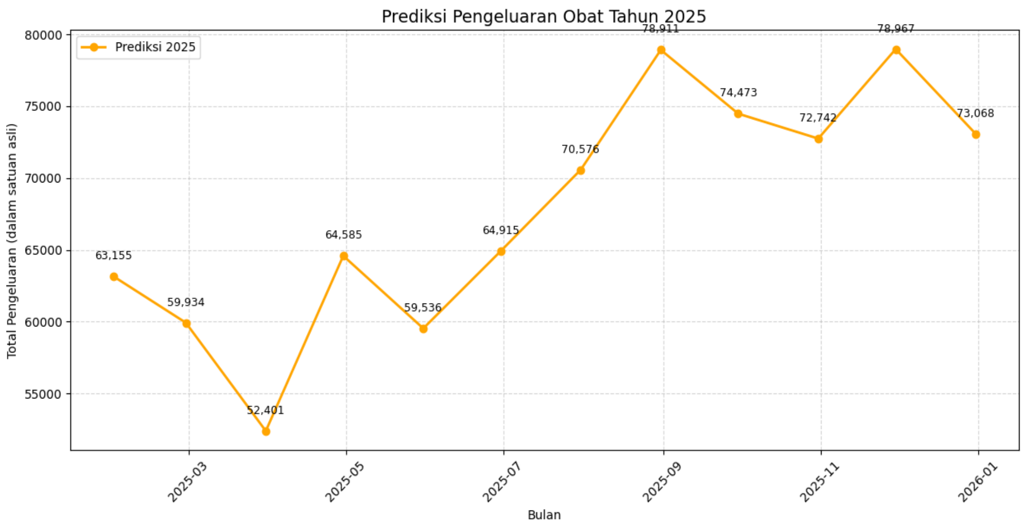

Figure 5. 2025 Drug Expenditure Prediction

The graph shows a tendency for increased demand in certain months, which also appeared seasonally in previous years. The visualization of the forecast results in Figure 5 shows fluctuations in drug expenditure that tend to increase in the middle to late 2025. The horizontal axis represents the time period (months), while the vertical axis shows the total drug expenditure in tablets. The orange line depicts the Prophet model's prediction results. The legend helps distinguish the forecasting line from the actual data. The values at each point show the amount of predicted expenditure each month, with peak expenditure recorded in August and November. This visual presentation makes it easier for readers to understand the seasonal patterns and medium-term trends generated by the model.

3.4. Model Evaluation

To assess the model's performance, an evaluation was conducted using two error metrics:

a) Mean Absolute Error (MAE): Measures the average absolute difference between actual and predicted values.

b) Mean Absolute Percentage Error (MAPE): Measures the average relative error in percentage form.

The evaluation results show:

a) MAE = 3,621.25

b) MAPE = 4,93%

Table 4. Prophet Model Evaluation Values

Metric	Value	Interpretation
MAE	3,621.25	Average absolute prediction error ≈ 7.637
MAPE	4,93	Prediction error rate < 10% (very good)

A MAPE value below 10% indicates that the model has a high level of accuracy in predicting drug expenditures and obtained a MAE value of 3,621.25 with an average absolute difference in predictions of around 7,637 units. Since MAE is expressed in the same units as the original data, these results show that the level of prediction error is relatively small compared to the overall scale of drug expenditure. Overall, the forecasting model used can be categorized as having good performance and is suitable as a reference in supporting future drug requirement planning.

In addition, Prophet also generates visualizations of trend and seasonal component decomposition:

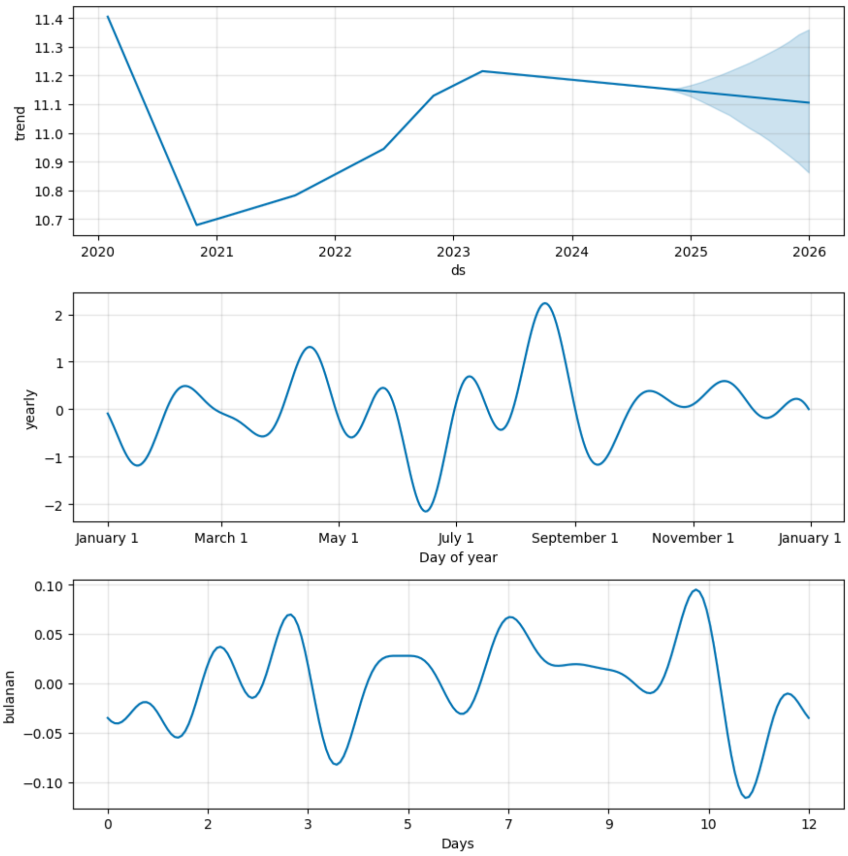

Figure 6. Decomposition of trend and seasonal components of the Prophet model for drug spending in 2020–2025

Figure 6. The trend component (top panel) shows that drug expenditure declined sharply in early 2021, most likely due to distribution policy adjustments and activity restrictions during the COVID-19

pandemic. After that period, the trend shows a steady increase from 2022 to 2024, indicating a recovery in health service activities and an increase in the demand for drugs in service facilities. The projection for 2025 shows a flat trend with a slight degree of uncertainty, as indicated by the light blue confidence interval.

The annual seasonal component (middle panel) shows a repeating pattern with several major peaks in May and September. This pattern indicates a surge in drug spending in the middle of the year, which is likely related to an increase in seasonal illnesses such as influenza or fever due to weather changes. The monthly seasonal component (bottom panel) shows small variations that reflect routine fluctuations between months, with a sharp increase in weeks 10 to 12, which is consistent with the annual demand pattern.

This visualization reinforces previous numerical results that Prophet is capable of effectively capturing long-term trends and short-term seasonal patterns. This decomposition capability makes Prophet useful not only as a prediction tool, but also as an instrument for analyzing drug consumption patterns that can support strategic decision-making in the field of pharmaceutical logistics management.

3.5. Discussion

The results of the study show that the Facebook Prophet model is capable of providing high accuracy in predicting Paracetamol tablet expenditure with a MAPE value of 4,93% and MAE of 3,621.25. The MAE and MAPE values obtained indicate a relatively small level of forecasting error compared to actual data, indicating that the model is able to capture historical patterns well. Practically speaking, the smaller the MAE and MAPE values, the higher the reliability of the model in providing predictions that are close to reality. This is very important in the context of drug management, because small errors in forecasting can have a direct impact on stock availability and pharmaceutical budget efficiency. According to Junianto [25], MAPE criteria of <10% are categorized as highly accurate predictions, so the results of this study confirm that Prophet can be used effectively in planning pharmaceutical logistics needs. This finding supports previous research by Cato Chandra [31] and Kwarteng [10], which demonstrated Prophet's superiority over traditional methods such as ARIMA, particularly in handling data with trend and seasonal patterns.

The application of Prophet in this study provides added value because this method is able to break down data into trend, seasonal, and residual components [15]. This is important in the context of pharmacy, given that demand for drugs is often influenced by seasonal factors, such as an increase in the need for analgesic drugs when there is an increase in cases of fever and influenza [32]. The visualization results of the seasonal component also show certain patterns relevant to public health conditions, which can be used as a basis for formulating drug supply strategies in the future . Based on these results, this model not only functions as a predictive tool, but also provides a deep understanding of drug usage patterns.

Analysis of the visualization results shows that the increase in drug expenditure tends to occur from March to July. This pattern can be interpreted as the impact of an increase in seasonal diseases such as respiratory tract infections, fever, and flu, which usually spike during the rainy season [3]. Meanwhile, the decline in spending from November to January is most likely due to reduced healthcare activities at the end of the year and the process of adjusting the new budget. Thus, the trend pattern generated by Prophet is in line with epidemiological and administrative dynamics in the field.

When compared to the manual method of moving averages, Prophet shows better performance with lower errors. This is in line with Kristiyanti's report [33], which found that conventional methods often fail to capture complex seasonal variations in inventory data. In addition, other research in the field of public health also emphasizes that innovations in public health services that use machine learning, AI, and big data are capable of providing accurate analytical data, improving the efficiency of strategic decision-making in disease surveillance and prevention [34]. This shows that integrating Prophet into the pharmacy management system has the potential to improve resource allocation efficiency and reduce the risk of drug shortages or excess stock.

Furthermore, the use of Prophet in this study also confirms the importance of the data pre-processing stage. The historical data used came from 2020–2024 drug expenditure documentation reports, which were first cleaned and reformatted to suit the model's needs. This is in line with the findings of Onassis Yusuf Inonu [35], which emphasize that the quality of data input plays a major role in determining the accuracy of prediction models. This study also shows that accurate predictions are not only determined by the method, but also by the quality and completeness of the data used.

From a practical standpoint, the application of Prophet in this study proves that the model can be used as a tool in planning drug requirements at the regional level. Research by Ismedsyah and Sri Rahayu states that planning pharmaceutical requirements using the right method can avoid drug shortages and low planning deviations (9.15%), which is better than the standard of 20-30%. This shows that a valid planning method can significantly reduce the risk of drug shortages [36]. With the support of trend and prediction graph visualizations, the results of this study are also easier to understand by non-technical decision makers in the health sector.

Overall, this discussion shows that Prophet not only provides accurate results but also offers strategic insights into medication usage patterns. The findings of this study contribute to the development of a more adaptive, accurate, and technology-based pharmaceutical logistics planning system, while also closing the existing research gap, namely the limited use of modern methods in predicting medication needs at the regional healthcare service level. The accurate predictions generated by the Prophet model can be used as a basis for strategic decision-making by the Pharmacy Installation in determining the volume of drug procurement and allocating the annual budget more efficiently.

4. Conclusion

This study aims to address the limitations of manual methods in planning drug requirements in Pharmacy Installations by applying the Python-based Facebook Prophet method. The results show that this model is capable of predicting Paracetamol tablet expenditure with a high level of accuracy, as indicated by a MAPE value of 4,93% and a MAE of 3,621.25, which, according to Junianto [25], is classified as highly accurate. The smaller the MAE value, the better the prediction quality because the average error between the actual value and the prediction is closer to zero. This is in line with the initial objective of the study outlined in the introduction, namely to produce more reliable predictions than manual methods, which often result in overstocking and stockouts.

In addition to providing good accuracy, Prophet also successfully identified trend and seasonal patterns in drug expenditure data, thereby providing strategic insights into pharmaceutical logistics planning. These findings confirm that the application of modern data-based methods can improve budget efficiency and reduce the risk of stockouts and overstocking, which were previously major obstacles in drug management.

The prospects for further research are wide open, particularly by expanding the scope to other types of drugs, integrating external variables such as health policies or disease trends, and combining Prophet with other algorithms such as LSTM or XGBoost to improve prediction performance. Additionally, the results of this research have the potential to be implemented in digital-based pharmaceutical management information systems, thereby supporting faster, more accurate, and adaptive decision-making processes in various healthcare facilities.

4.1. Research Limitations

This study has several limitations that need to be considered. First, the data used only covers one type of drug, namely paracetamol tablets, so the prediction results cannot be generalized to all types of drugs managed by the Pharmacy Installation. Second, the scope of the study is limited to one institution, so it does not consider variations in drug needs in other regions with different demand characteristics.

4.2. Recommendations and Research Contributions

For further research, it is recommended to develop a hybrid Prophet–LSTM model or integrate the forecasting results into a real-time drug stock prediction dashboard so that it can be directly utilized by pharmaceutical management. In addition, research can be expanded to various types of drugs and other regions to obtain more comprehensive results.

In practical terms, this research contributes to the efficiency of pharmaceutical logistics management, particularly in the areas of procurement planning and drug stock control based on historical data. The implementation of the Prophet model can help minimize the risk of stock shortages or surpluses, while supporting data-driven decision-making in the health sector. From an academic perspective, this research enriches the literature on the application of machine learning in the fields of pharmacy and regional public health management.

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